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An integrated synthetic value of fuzzy judgments and nonlinear programming methodology for ranking the facility layout patterns

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ABSTRACT

In this paper, the goal is to incorporate qualitative criteria in addition to quantitative criteria to facility layout design (FLD) problem. To this end, we present an integrated methodology based on the synthetic value of fuzzy judgments and nonlinear programming (SVFJ–NLP). The facility layout patterns (FLPs) together with their performance measures of total cost of material handling are generated by a computer-aided layout-design tool, CRAFT. Also, the performance measures of second quantitative criterion (construction cost of width walls) are calculated by appraising these FLPs. The SVFJ is then applied to collect the performance measures related to qualitative criteria and finally, a non-linear programming (NLP) model is proposed to solve the FLD. Results obtained from a real case study validate the effectiveness of the proposed model.

1. Introduction

A FLD problem is applied for determining the location of facilities or departments, directly, influences the total cost of manufacturing a product or offering a service, in view of the governing constraints or objectives. Although in manufacturing industrials, the material handling cost (the material handling cost is determined based on the flow of materials and the distances between departments) is the most important factor for determining the efficiency of layout and it encompasses 20–50% of the total operating cost and 15–70% of the total cost for manufactured goods (Tompkins et al., 1996), other important criteria may affect the selection of facility layout. Inappropriate facility layout can cause the major time and cost overruns (Liang & Chao, 2008; Pardalos & Du, 1998). Hence, a FLD depends on the number of objectives and criteria such as the adjacency of facilities, distance between facilities, locations of facilities, flexibility and accessibility. The FLD problem has different formulations such that it can be solved by existing approaches of optimization. Most of plant layout design literatures are either algorithmic or procedural (Yang & Hung, 2007). Over the past 20 years, numerous papers were proposed to solve the different FLD problems.

The optimization problems include assigning the facilities or departments within the spaces, in view of becoming one objective or multi-objectives and related constraints in the problem. When the factory site is divided into the rectangular grids (discrete) and each of facilities adopts one or more of these grids, it is often considered as Quadratic Assignment Problems (QAPs). The QAP goal is to minimize the distance-based transportation cost which is expressed as the quantity of workflow and the traveled distance. Although, the QAP can be solved by approaches such as cutting plane, branch and bound or other operations research techniques, finding the optimal solutions for practical QAP instances still seems extremely challenging from both theoretical results and practical experience. Also, unfortunately these problems belong to the class of NP-hard (Sahni & Gonzalez, 1976) and it is addressed as one of the hardest problems that is almost impossible to be optimally solved in an acceptable time for more than 25 facilities/cells (Solimanpur, Vrat, & Shankar, 2004), particularly, when the important qualitative criteria affects FLD, it results in prohibitive computation time for large problems (Ertay, Ruan, & Tuzkaya, 2006). In many articles, the layout representation is continual (Heragu & Kusiak, 1990), where the FLD problem is often formulated as Mixed Integer Programming (MIP). In these models, each facility is represented as a rectangle of known sizes, while inter-facility distances are defined as the rectilinear distances between facility centers. Both exact algorithms and heuristics have been developed to solve continuous facility layout (CFL) problem.

The exact approaches often obtain the optimal solutions. When equal-sized and rectangular-shaped facilities are considered, the exact solution can be obtained for small problem sizes (for example, 15–20 facilities), in a reasonable time (Moghaddain & Shayan, 1998). Also, these approaches can be applied for CFL (Xie & Sahinidis, 2008), dynamic layout problem (DLP) (Rosenblatt, 1986) and other problems.

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The near-optimal methods can generally be classified into two classes, namely heuristics and metaheuristics. Heuristic methods are grouped into two groups including the procedural approaches such as systematic layout planning (SLP) (Muther, 1973) and constructed algorithmic approaches as ALDEP (Seehof & Evans, 1967) and improved as CRAFT (Armour & Buffa, 1963). Among the approaches based on metaheuristics, one can distinguish global search methods (Chiang & Kouvelis, 1996), simulated annealing (Chwif, Pereira Barretto, & Moscato, 1998), genetic algorithm (Azadivar & Wang, 2000; Mavridou & Pardalos, 1997) and ant colony algorithms (Baykasoglu, Dereli, & Sabuncu, 2006). The great advantage of these methods is to avoid being caught in local optima by sometimes accepting moves that worsen the objective function (Chwif et al., 1998). Unfortunately, the metaheuristics approaches may be complex and, sometimes, their learning is difficult for factory designers.

When some qualitative criteria together with the quantitative criteria are accommodated with a FLD problem, it can be solved by multi-attribute decision making (MADM) techniques. For example, Cambron and Evans (1991), Foulds and Partovi (1998) and Yang, Su, and Hsu (2000) applied AHP to evaluate the design patterns. Yang and Kuo (2003) applied an integrated AHP–DEA methodology for ranking FLPs, where the AHP and the spiral commercial software were used for generating the performance measures of the qualitative criteria and determining the performance measures of the quantitative criteria, respectively, and finally DEA was applied for solving the layout performance frontiers problem simultaneously by considering both the quantitative and qualitative data. However, they inserted the measures of qualitative criteria for ranking FLPs while solving FLD, the used DEA model might ignores the scores of some criteria in total score. Furthermore, Yang and Hung (2007) presented the fuzzy technique for order preference by similarity to ideal solution (FTOPSIS) for ranking the FLPs and then the obtained results were compared with TOPSIS and YK-model.

In this paper, we present an integrated methodology based on the SVFJ–NLP for ranking the FLPs generated by commercial CRAFT software. Here the qualitative criteria data are obtained by SVFJ and quantitative data earned by commercial software and by designers, respectively. Besides, an NLP model is proposed to solve the layout design problem.

The remainder of this paper is organized as follows. In Section 2, the proposed model is presented for ranking the FLPs. An illustrative example is presented to implement the proposed model in Section 3 and finally, in Section 4, conclusions and limitation are given.

2. The proposed model

Fig. 1 represents the framework of the proposed model. As we see, at first the input data needed for CRAFT software regarding to the departments and the relations between them. After entering the data and by implementing program, several FLPs with their related total cost of handling material (TCHM) will be achieved as the output. In fact, these costs are the performance measures of the first intended quantitative criterion. Since in a produced FLP, each department is printed in different numbers of digits, due to different areas, it is possible that width and length of internal horizontal and vertical walls of factory alter, respectively, during the exchanging the location of two departments. Such an alteration of dimensions will be caused the change of initial (construction) investment. Hence, this quantitative criterion will certainly effect the evaluations of a FLP by designers. On the other hand, it may be noticeable from the designers' viewpoint that in addition to the quantitative criteria, other significant qualitative criteria such as flexibility, facilitation of handling (FH) and accessibility, can influence the arrangement appraisal of a FLP. In this study, we use SVFJ approach in order to determine the performance measures of such criteria. It is performed via assessments of different FLPs based on designers' opinion. After we achieved the performance measures against all FLPs for both criteria, an NLP model is proposed to rank FLPs based on these measures and the final design is chosen with the higher score as the optimum FLP. Before introducing the above-mentioned methodology, the concept of fuzzy set theory should be first explained.

2.1. Fuzzy set theory

It is clear that from its origin, decision making as a serious task in the field of management, has been confronted with uncertainty and continuous change in defining and determining the effective qualitative factors of forming decision. To this end, to deal quantitatively with imprecision or uncertainty, fuzzy set theory is primarily concerned with vagueness in human thoughts and perceptions (Beskese, Kahraman, & Irani, 2004). Fuzzy set theory, which was first introduced by Zadeh in 1965, is quite similar to man's attitude. By using this theory, the vague statements, such as "approximately", "very", and "nearly", can be transformed into the quantitative numbers and then a complicated decision making problem is solved. A major contribution of fuzzy set theory is its capability in representing the vague data (Amin & Razmi, 2009). The momentous duty that the classic set in crisp quantitative values form is not able to correct decision making. In spite of the classic set only with two situations 0 and 1, in this theory, the membership degree of an element is between 0 and 1. In this paper, FLPs are ranked regarding to the qualitative criteria by using the concept of fuzzy theory in SVFJ based on the designer judgments.

Here, we define the fuzzy set, triangular fuzzy number, linguistic variables and some the algebraic calculations to use in continuance of discussion (Kaufmann & Gupta, 1991; Zimmermann, 1991).

Definition 2.1. A fuzzy set $\widetilde{B}$ in a universe of discourse Y is showed by a membership function $\mu_{\widetilde{B}}(y)$ in which $\forall y \in Y$ assigns a real number in the closed interval $[0,1]$. $\mu_{\widetilde{B}}(y)$ introduce the membership degree of y in $\widetilde{B}$.

Definition 2.2. A triangular fuzzy number $\widetilde{B}$ which is indicated as a triplet (l_1, l_2, l_3) is defined with piecewise linear membership function $\mu_{\widetilde{B}}(y)$ as follows:

$$\mu_{\widetilde{B}}(y) = \begin{cases} (y - l_1)/(l_2 - l_1), & l_1 \leqslant y \leqslant l_2, \\ (l_3 - y)/(l_3 - l_2), & l_2 \leqslant y \leqslant l_3, \\ 0, & \text{otherwise}, \end{cases}$$

where l_1, l_3 are the lower and upper bounds, respectively, and l_2 is the most likely value of $\widetilde{B}$.

Definition 2.3. Let $\widetilde{A} = (l_1, l_2, l_3)$ and $\widetilde{B} = (m_1, m_2, m_3)$ are two positive triangular fuzzy numbers and k is a positive real number. Then, sum, multiplication, subtraction of these two fuzzy numbers is showed as follows:

$$\widetilde{A} \oplus \widetilde{B} = [l_1 + m_1, l_2 + m_2, l_3 + m_3]$$

$$\widetilde{A} \otimes \widetilde{B} = [l_1 \times m_1, l_2 \times m_2, l_3 \times m_3]$$

$$\widetilde{A} \ominus \widetilde{B} = [l_1 - m_3, l_2 - m_2, l_3 - m_1]$$

$$\widetilde{A} \otimes k = [l_1 \times k, l_2 \times k, l_3 \times k]$$

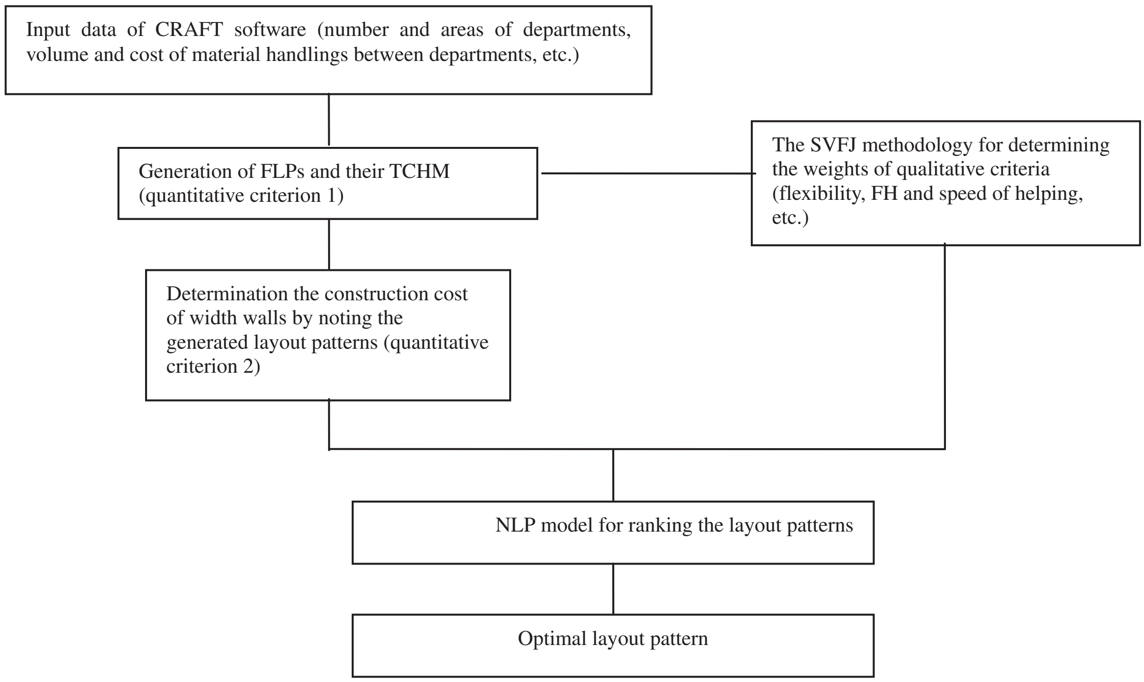

Fig. 1. The proposed SVFJ–NLP methodology.

Definition 2.4. Fuzzy variables are highly suitable for expressing of decision makers' subjective judgments on the issues which have the qualitative criteria. These variables apply the fuzzy numbers for prioritizing and ranking. In this paper, by converting these variables into the triangular fuzzy numbers, we can assess the FLPs related to the qualitative criteria.

2.2. CRAFT software

CRAFT which was first introduced by Armour and Buffa (1963) is a quantitative approach for FLD problems. Input data into the software include initial FLP, volume travel from–to chart, unit cost between departments from–to chart, distance between departments from–to chart, fixed departments, number and area of departments, length and width of factory, number of bays and selecting the desired method for calculating the distance between departments (Rectilinear or Euclidean). CRAFT can be implemented as binary, ternary, binary and then ternary and ternary and then binary alternatives. It is noticeable that we apply binary exchange alternative in order to improve FLPs. Generally, improvement process in CRAFT computerized algorithm can be summarized in the following six steps:

Step 1: Computation of the department centers and distance between them based on rectangular method.

This step is used to determine the distance between departments from–to chart.

Step 2: Computation of the TCHM from–to chart.

This chart is achieved by multiplying three charts: distance, traveled volume and unit cost.

Step 3: Determination of possible exchanges and calculation of their approximate costs.

In this stage, the possible binary exchanges including neighboring departments or departments with equal areas are first determined and then the estimation cost is computed only via exchanging the coordinate centers and not exchanging the real location of two departments.

Step 4: Continue or stop of improvement.

If all estimated costs in prior step are more than or equal to TCHM of initial proposed FLP, the improvement process is stopped and initial FLP is chosen as optimum FLP; otherwise, an exchange is selected which had the least estimation cost.

Step 5: Determination of real cost.

By real exchanging the location of two departments chosen in step 4, the new distance from–to chart is reconstructed and then the real total cost is recomputed.

Step 6: Process iteration.

By keeping the real cost of above-improved FLP as current score, steps 3–6 are again repeated.

2.3. Determining the quantitative criteria

The discussed quantitative criteria of the study include two cost-type criteria. The first cost which is, in fact, the same popular TCHM regarding to each FLP, is generated by CRAFT itself after inputting of data and its implementation. The second cost includes the expenses related to construction of internal horizontal or vertical walls of factory. In each pairwise exchange of departments, due to the different areas of departments, it is possible that walls are constructed with less or more lengths (widths) and it will inevitably affect initial construction cost of each FLP. Computation of the total construction cost of internal vertical or horizontal walls in each pattern is easily achieved by counting the number wall digits between departments, then multiplying by measured area of each scaled digit, by height of factory and finally by construction cost for each square meter.

2.4. Determining the weights of qualitative criteria

One of the most important issues of decision-making is prioritization of criteria (alternatives). Particularly, determining the importance of weights of qualitative criteria by managers as compared to the issue of the discussion in this paper is subjective in such a way that managers usually select some important criteria (alternatives) and then prioritize them.

The qualitative criteria considered by designers include flexibility, FH and speed of helping (SH). Flexibility includes implementation of various works under different operational conditions and future expansion of each FLP. Owing to the fact that based on designers' point of view, the movement paths of material handling equipments, as much as possible should be direct and have the least number of cycles with high angles in order to expedite the movement and decrease the traffic and probable events, the criterion of FH is considered and ultimately other criterion named SH are noticed, too. This criterion can be important in necessary conditions (e.g. the occurrence of an event and/or lack of human resources, specifically in production, reception and dispatch store departments). The following methodology of determining the weights is presented for these criteria using designers' judgments based on fuzzy data.

There are several methods for determining the weights of criteria (alternatives) in which the analytic hierarchy process (Saaty, 1980) is the most popular. For comparing the C criteria (R alternatives), it is difficult to construct a consistent pairwise comparison matrix when the number of alternatives or criteria is quite big (Wang, Liu, & Elhag, 2008). Hence, we apply the subsequent SVFJ approach (which is dealt with in detail in the next subsection) for obtaining the weights of FLPs with respect to each qualitative criterion c ($c = 1,\ldots,C$) using five linguistic variables, which are shown with their triangular fuzzy numbers in Table 1.

2.4.1. The SVFJ method for prioritizing the FLPs for each criterion

2.4.1.1. Constructing the fuzzy assessment matrices for each criterion. Without loss of generality, let FLP i ($i = 1,\ldots,R$) regarding to criterion c ($c = 1,\ldots,C$) is to be assessed by n ($n = 1,\ldots,N$) designers. After compiling the all appraisals of N designers related to importance of FLP i ($i = 1,\ldots,R$) against criterion c ($c = 1,\ldots,C$) by selecting the above-mentioned linguistic variables, we construct the fuzzy assessment matrix for each criterion c as shown in Table 2.

Where $w_{ic}^n = (Lw_{ic}^n, Mw_{ic}^n, Uw_{ic}^n)$ is the weight of FLP i under cth criterion which is determined by selecting the linguistic variables introduced in Table 1 by nth ($n = 1,\ldots,N$) designer and Lw_{ic}^n, Uw_{ic}^n and Mw_{ic}^n are the lower, upper bounds and most likely value of triangular fuzzy numbers.

2.4.1.2. Obtaining a single fuzzy weight for each FLP. Here, all assessments with respect to FLP i by N experts under criterion c are integrated to a single fuzzy weight using Eq. (1):

$$\tilde{w}_{ic} = (1/N) \otimes \left(\tilde{w}_{ic}^1 \oplus \tilde{w}_{ic}^2 \oplus \cdots \oplus \tilde{w}_{ic}^N\right) \quad i = 1,\ldots,R,\ \ c = 1,\ldots,C \tag{1}$$

Table 2
Fuzzy judgment matrix for cth criterion.

Designers	FLP_S				
	FLP_1	$\cdots$	FLP_r	$\cdots$	FLP_R
A_1	w_{1c}^1	$\cdots$	w_{rc}^1	$\cdots$	w_{Rc}^1
$\vdots$	$\vdots$		$\vdots$		$\vdots$
A_n	w_{1c}^n	$\cdots$	w_{rc}^n	$\cdots$	w_{Rc}^n
$\vdots$	$\vdots$		$\vdots$		$\vdots$
A_N	w_{1c}^N	$\cdots$	w_{rc}^N	$\cdots$	w_{Rc}^N

where $\tilde{w}_{ic}$ is obtained the single fuzzy weight for FLP i under criterion c and N is the numbers of the designers.

Also, $\tilde{w}_{ic}$ as a fuzzy number can be represented by triangular membership function as follows:

$$\tilde{w}_{ic} = (Lw_{ic}, Mw_{ic}, Uw_{ic}) \quad i = 1,\ldots,R,\ \ c = 1,\ldots,C \tag{2}$$

According to Buckley (1985), the three end points, namely Lw_{ic}, Mw_{ic} and Uw_{ic} can be computed as follows:

$$Lw_{ic} = \frac{\left(\sum_{n=1}^{N} Lw_{ic}^n\right)}{N} \tag{3}$$

$$Mw_{ic} = \frac{\left(\sum_{n=1}^{N} Mw_{ic}^n\right)}{N} \tag{4}$$

$$Uw_{ic} = \frac{\left(\sum_{n=1}^{N} Uw_{ic}^n\right)}{N} \tag{5}$$

2.4.1.3. Defuzzification. After obtaining a single fuzzy weight for FLP i under criterion c, this should be transformed into a nonfuzzy number to use in NLP model. Defuzzification is a technique to convert the fuzzy number into crisp real numbers (Tsaur, Chang, & Yen, 2002). The procedure of defuzzification (Hsieh, Lu, & Tzeng, 2004; Opricovic & Tzeng, 2003) locates the Best Nonfuzzy Performance value (BNP). Most of popular methods used in such a defuzzified ranking generally are the mean of maximal (MOM), center of area (COA), and α-cut (Zhao & Govind, 1991). In this paper, we adopt the COA using the following equation:

$$\text{BNP}_{ic} = \frac{[(Uw_{ic} - Lw_{ic}) + (Mw_{ic} - Lw_{ic})]}{3} + Lw_j \quad i = 1,\ldots,R,\ \ c = 1,\ldots,C \tag{6}$$

where BNP_{ic} is the Best Nonfuzzy Performance value of the FLP i with respect to criterion c and Lw_{ic}, Mw_{ic} and Uw_{ic} are calculated as Eqs. (3)–(5), respectively.

2.5. The proposed NLP model for ranking the FLPs

In this paper, we propose the following NLP model for ranking the FLPs. The proposed NLP model is flexible such that it can easily

Table 1
Fuzzy linguistic variables and their corresponding triangular fuzzy numbers.

Triangular fuzzy number	Linguistic variable
(0, 0.1, 0.3)	Very low
(0.1, 0.3, 0.5)	Low
(0.3, 0.5, 0.7)	Medium
(0.5, 0.7, 0.9)	High
(0.7, 0.9, 1)	Very high

Table 3
The departments name and their area.

No	Department name	Area (m^2)
1	Production	1200
2	Reception warehouse	1500
3	Dispatch warehouse	1400
4	Quality control	400
5	Maintenance	300
6	Office section	900
7	Loss warehouse	300

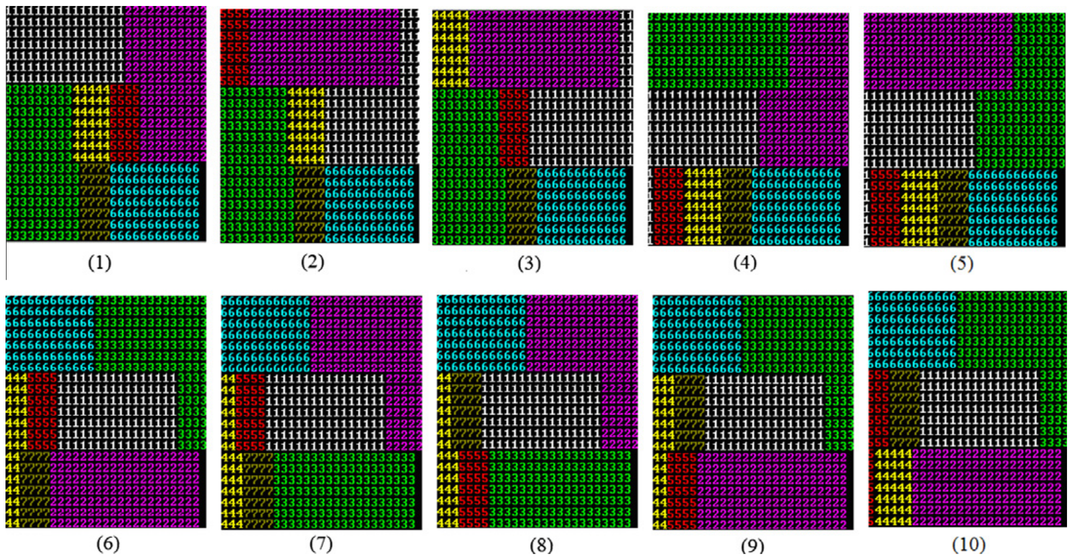

Fig. 2. The FLPs generated by CRAFT software.

integrate additional information from experts to solve FLD problem. The purpose is to aggregate multiple performance scores of a FLP with respect to different criteria into a single score for the subsequent FLD problem:

$$\max \quad \alpha \tag{7}$$

$$\text{s.t.} \quad \alpha \leqslant \sum_{c=1}^{C} \upsilon_{ic} w_c, \quad i = 1, 2, \ldots, R \tag{8}$$

$$\sum_{c=1}^{C} w_c^2 = 1, \tag{9}$$

$$w_C \geqslant w_{C-1} \geqslant \cdots \geqslant w_1 \geqslant 0, \quad c = 1, 2, \ldots, C \tag{10}$$

The above NLP model maximizes the minimum of the total scores of the FLPs and determines a common set of weights for all FLPs. Constraint (9) prevents the weight of a FLP to become zero even against an unimportant criteria and constraint (10) represents the order of criteria ranking by designers.

It is worth nothing that since the objective function of above optimization model is maximization, for cost-type criteria such as TCHM, we should apply the scale transformation as below:

$$\frac{\max_{i=1,2\ldots,R}\{\upsilon_{ic}\} - \upsilon_{ic}}{\max_{i=1,2\ldots,R}\{\upsilon_{ic}\} - \min_{i=1,2\ldots,R}\{\upsilon_{ic}\}} \tag{11}$$

and, for those criteria that are benefit-type such as flexibility, we use the scale transformation:

$$\frac{\upsilon_{ic} - \min_{i=1,2\ldots,R}\{\upsilon_{ic}\}}{\max_{i=1,2\ldots,R}\{\upsilon_{ic}\} - \min_{i=1,2\ldots,R}\{\upsilon_{ic}\}} \tag{12}$$

Table 5
The fuzzy judgments of designers for FH.

	FLPs									
	1	2	3	4	5	6	7	8	9	10
Designer 1	VL	VL	VL	VH	H	H	M	VH	H	VH
Designer 2	L	VL	L	VH	H	M	VH	H	M	H
Designer 3	M	L	VL	M	VH	VH	VH	M	VH	M
Designer 4	VL	M	L	H	VH	H	H	VH	H	H
Designer 5	L	L	VL	M	H	VH	M	M	H	VH
Designer 6	L	VL	VL	VH	VH	H	VH	L	M	M
Designer 7	VL	L	M	VH	H	M	H	H	M	H
Designer 8	M	VL	M	M	M	H	L	M	VH	VH

The advantage of the proposed NLP model is that, it considers all criteria and assigns a nonzero weight to each criterion.In general, we can obtain the score of each FLP by following stages:

1. Transform the performance measures of cost-type criteria using $\frac{\max_{i=1,2\ldots,R}\{\upsilon_{ic}\}-\upsilon_{ic}}{\max_{i=1,2\ldots,R}\{\upsilon_{ic}\}-\min_{i=1,2\ldots,R}\{\upsilon_{ic}\}}$ and the measures of benefit-type criteria using $\frac{\upsilon_{ic}-\min_{i=1,2\ldots,R}\{\upsilon_{ic}\}}{\max_{i=1,2\ldots,R}\{\upsilon_{ic}\}-\min_{i=1,2\ldots,R}\{\upsilon_{ic}\}}$ to a common scale between 0 and 1.
2. To obtain the score of each FLP, solve the FLD problem for each FLP by a nonlinear optimizer.
3. Sort the scores S_i in a descending order.

3. Case study

In this section, to show applicability of the proposed methodology, a real example from a production company is adopted, which

Table 4
The fuzzy judgments of designers for Flexibility.

	FLPs									
	1	2	3	4	5	6	7	8	9	10
Designer 1	L	M	H	H	VH	L	VL	VL	L	H
Designer 2	L	M	M	VH	VH	L	VL	L	VL	VL
Designer 3	VL	L	L	VH	VH	VL	VL	M	L	H
Designer 4	M	M	L	M	H	L	L	VL	L	VL
Designer 5	M	L	M	VH	VH	VL	VL	VL	M	M
Designer 6	L	L	M	H	H	VL	VL	L	L	VL
Designer 7	VL	H	L	VH	VH	L	L	VL	VL	L
Designer 8	VL	L	M	H	VH	VL	VL	M	H	L

Table 6
The fuzzy judgments of designers for SH.

	FLPs									
	1	2	3	4	5	6	7	8	9	10
Designer 1	M	VL	H	VH	VH	M	M	H	VH	VH
Designer 2	L	L	M	H	H	H	L	L	M	H
Designer 3	VL	M	VL	VH	M	VL	H	M	M	M
Designer 4	L	H	M	VH	VH	L	L	L	H	L
Designer 5	M	VL	L	M	VH	H	H	M	M	VH
Designer 6	H	VL	L	H	VH	VL	L	H	H	H
Designer 7	L	M	M	H	VH	H	M	VH	M	H
Designer 8	VL	M	VL	VH	H	VL	VL	M	H	M

Table 7
The SVFJ and BNP of Layout patterns for the qualitative criteria.

Layout pattern	Flexibility	BNP	FH	BNP	SH	BNP
1	(0.112, 0.275, 0.475)	0.287	(0.112, 0.275, 0.475)	0.287	(0.175, 0.350, 0.550)	0.358
2	(0.225, 0.425, 0.625)	0.425	(0.075, 0.225, 0.425)	0.241	(0.187, 0.350, 0.550)	0.362
3	(0.250, 0.450, 0.650)	0.450	(0.100, 0.250, 0.450)	0.266	(0.200, 0.375, 0.575)	0.383
4	(0.575, 0.775, 0.925)	0.758	(0.525, 0.725, 0.875)	0.708	(0.575, 0.775, 0.925)	0.758
5	(0.650, 0.850, 0.975)	0.825	(0.550, 0.750, 0.912)	0.737	(0.600, 0.800, 0.937)	0.779
6	(0.050, 0.200, 0.400)	0.216	(0.500, 0.700, 0.875)	0.691	(0.237, 0.400, 0.600)	0.412
7	(0.025, 0.150, 0.350)	0.175	(0.475, 0.675, 0.837)	0.662	(0.237, 0.425, 0.625)	0.429
8	(0.100, 0.250, 0.450)	0.266	(0.425, 0.625, 0.800)	0.616	(0.325, 0.500, 0.687)	0.504
9	(0.150, 0.325, 0.525)	0.333	(0.475, 0.675, 0.850)	0.666	(0.425, 0.625, 0.937)	0.662
10	(0.187, 0.350, 0.550)	0.363	(0.525, 0.725, 0.887)	0.712	(0.362, 0.537, 0.700)	0.533

Table 8
The measures of FLPs with respect to all criteria.

Layout patterns	TCHM ($)	CCWW ($)	Flexibility	FH	SH
1	936.960	23,112	0.287	0.287	0.358
2	894.730	26,964	0.425	0.241	0.362
3	837.039	27,606	0.450	0.266	0.383
4	817.967	28,890	0.758	0.708	0.758
5	809.195	29,532	0.825	0.737	0.779
6	763.796	30,816	0.216	0.691	0.412
7	749.966	30,174	0.175	0.662	0.429
8	733.413	30,174	0.266	0.616	0.504
9	705.463	30,816	0.333	0.666	0.662
10	702.538	31,458	0.363	0.712	0.533
Max	936.960	31,458	0.825	0.737	0.779
Min	702.538	23,112	0.175	0.241	0.358

it is in stage of its departments design. First, Table 3 shows the details as compared to name and area of departments.

Also, the different FLPs generated by CRAFT commercial software, are exhibited in Fig. 2. As we see, FLP 1 is the initial sequence proposed based on experts' point of views and reminder FLPs are generated by pairwise exchange between departments in any iteration of program.

By inaugurating the separate sessions, the fuzzy numbers are selected (as presented in Table 2) by each expert. Tables 4–6 show the opinion of experts for each FLP. These judgments are transformed into a synthetic triangular fuzzy number using Eq. (2) and then are defuzzfied to the nonfuzzy measures (BNP) using Eq. (6). Table 7 displays the synthetic fuzzy judgments and BNP value obtained by eight designers.

As mentioned before, the five criteria which were considered in assessment process of generated FLPs, include three qualitative criteria: flexibility, FH and SH as well as two quantitative criteria: TCHM and construction cost of width walls (CCWW). The last criterion regarding to FLPs is obtained as discussed in Section 2.2, where the area of each digit yield by dividing the area of a given department to the number of its scaled digits. By implementing this, the area of each digit is 10.72 m^2.Table 8 shows the performance measures of FLPs with respect to criteria. Since both quantitative criteria are cost-type criteria, i.e. they are negatively related to the importance level of a FLP, their measures are converted to a common scale by Eq. (11) and three qualitative criteria using Eq. (12). The measures of scale transformation are presented in Table 9.

Now, we can obtain the score of each FLP based on data in this table using NLP model introduced in Section 2.4 via the Microsoft Excel Solver or the LINGO software package, noting that the order of criteria ranking proposed by designers is as:

$$W_1 \geqslant W_4 \geqslant W_3 \geqslant W_2 \geqslant W_5$$

By solving the NLP model for each FLP, the obtained scores are arranged at scores column of Table 9 in a descending order. As we see, FLP 5 is the optimum FLP with score 1.396, whereas it had been lied on rank 6 with TCHM 809.195($), based on the ranking performed by CRAFT (only by considering the criterion of TCMH). The reason of ranking alternation is clear; this FLP under the qualitative criteria has very high performance measures. In contrast, FLP 10 which had been set on the first place in CRAFT ranking, with the least TCHM, stands in lower situation in ranking based on our approach, due to being low in performance measures with respect to criteria of CCWW and flexibility. By presenting the achieved results to designers, they approved the validity of such a ranking and when we asked their opinions about the high measures of FLP 5 under the qualitative criteria, they remarked about flexibility that external walls of departments can easily extend without destroying the internal walls. They mentioned that suitable movement in direct paths is the main reason of high measures related to FH. On the other hand, they verified which this FLP has higher SH in emergency situations when comparing to others.

4. Conclusions and limitations

It is crucial to design an efficient FLD problem in a production factory. Ignoring the significant criteria (especially, the qualitative criteria which are not easily stateable in the quantitative measures form) in design time will certainly result in increasing the costs, prices and ultimately decreasing the products' sale. In this study, using the SVFJ approach, we transformed the subjectivity subjects

Table 9
The measures of scale transformation and ranking the FLPs by our model.

Our rank	TCHM ($)	CCWW ($)	Flexibility	FH	SH	Scores	Rank by CRAFT
5	0.545	0.230	1.000	1.000	1.000	1.396	10
4	0.507	0.307	0.896	0.941	0.950	1.333	9
10	1.000	0.000	0.289	0.949	0.415	1.144	8
9	0.987	0.076	0.243	0.856	0.722	1.112	7
8	0.868	0.153	0.140	0.756	0.346	0.981	6
7	0.797	0.153	0.000	0.848	0.168	0.916	5
6	0.738	0.076	0.063	0.907	0.128	0.906	4
3	0.426	0.461	0.423	0.050	0.059	0.685	1
1	0.000	1.000	0.172	0.092	0.000	0.618	3
2	0.180	0.538	0.384	0.000	0.009	0.547	2

of designers (in linguistic variables form) against qualitative criteria which are stated by assessing printed FLPs in program output, to quantitative measures. These judgments occurred via erecting the distinct sessions in order to do not have any prejudice about other. Also we introduced the other quantitative criteria in addition to TCHM called construction cost, which is considered due to difference in the width walls of FLPs. Then, we ranked 10 FLPs regarding to these five criteria via a NLP model.

Here, it is significant to mention some points: first, in this study, we just considered the main sections (departments) to rank while each of those may include other subsections that were not taken into account in our study (e.g., production section may include office sections, work in progress, etc.). Second, by changing the initial sequence which designers used as input FLP in CRAFT, it is possible to produce other FLPs differed from FLPs presented in Fig. 2. Ultimately, owning to the fact that the performance measures of qualitative criteria achieved based on subjectivity judgments, these severely depend on such judgments and sometimes can result in inconsistent on behalf of designers.

But despite all these limitations, the proposed integrated SVFJ–NLP approach ranks the FLPs, is simple, efficient and applicable for any number of FLPs under any number of the qualitative and quantitative criteria.

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